Filtering Electrocardiographic Signals using filtered- X LMS algorithm

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***Abstract*— In this paper, a simple and efficient filtered- X Least Mean Square (FXLMS) algorithm is used for the removal of different kinds of noises from the ECG signal. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the noisy ECG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. Different filter structures are presented to eliminate the diverse forms of noise: baseline wander, 60 Hz power line interference, muscle artifacts and motion artifacts. Finally different adaptive structures are implemented to remove artifacts from ECG signals and tested on real signals obtained from MIT-BIH data base. Simulation studies shows that the proposed realization gives better performance compared to existing realizations in terms of signal to noise ratio.**

***Index Terms*— adaptive filtering, artifact, ECG, FXLMS, noise cancelation.**

I. INTRODUCTION

The extraction of high-resolution ECG signals from recordings contaminated with background noise is an important issue to investigate. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation. Many approaches have been reported in the literature to address ECG enhancement using adaptive filters [1]-[7], which permit to detect time varying potentials and to track the dynamic variations of the signals. In [3], Thakor et al. proposed an LMS based adaptive recurrent filter to acquire the impulse response of normal QRS complexes, and then applied it for arrhythmia detection in ambulatory ECG recordings. The reference inputs to the LMS algorithm are deterministic functions and are defined by a periodically extended, truncated set of orthonormal basis functions. In these papers, the LMS algorithm operates on an instantaneous basis such that the weight vector is updated every new sample within the occurrence, based on an instantaneous gradient estimate. In a study, however, a steady state convergence analysis for the LMS algorithm with deterministic reference inputs showed that the steady-state weight vector is biased, and thus, the adaptive estimate does not approach the Wiener solution. To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm [8], in which the coefficient vector is updated only once every occurrence based on a block gradient estimation. The BLMS algorithm has been proposed in the case of random reference inputs and has, when the input is stationary, the same steady state misadjustment and convergence speed as the LMS algorithm. In recent past, several ECG enhancement and monitoring techniques are presented [9]-[16], apart from these, several signal processing techniques are also presented [18]-[21]. Recently in [17] Rahman et al. presented several less computational complex adaptive algorithms in time domain, but these algorithms exhibits slower convergence rate.

In order to achieve high signal to noise (SNR) in this paper we propose filtered- X LMS algorithm for the cancelation of artifacts from ECG signals. The well-known filtered-X LMS-algorithm is, however, an adaptive filter algorithm which is suitable for adaptive noise cancelation applications. It is developed from the LMS algorithm, where a model of the dynamic system between the filter output and the estimate, i.e. the forward path is introduced between the input signal and the algorithm for the adaptation of the coefficient vector. In [22], Das et al. presented several forms of BFXLMS and its fast implementation using convolution and cross-correlation mechanics for active noise control systems. Some more modifications to FXLMS are also used with the same application [23]-[24]. Thus far, to the best of the author's knowledge filtered X LMS is not used in the contest of ECG signal noise cancelation. To study the performance of the proposed algorithm to effectively remove the noise from the ECG signal, we carried out simulations on MIT-BIH database for different noises. The simulation results shows that the proposed algorithm performs better than the LMS counterpart to eliminate the noise from ECG.

II. FILTERED-X LMS ALGORITHM FOR THE REMOVAL OF NOISE FROM ECG SIGNAL

To facilitate the development of the block filtered-X LMS algorithm, we considered a length L Least mean square (LMS) based adaptive filter shown in Fig. 1, that takes an input sequence x(n) and updates the weights as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, \mathbf{x}(n)\, e(n), \qquad (1)$$

where, $\mathbf{w}(n) = [\, w_0(n), w_1(n), \ldots, w_{L-1}(n)\,]^t$ is the tap weight vector at the n^{th} index, $\mathrm{x}(n) = [x(n)\, x(n-1) \ldots x(n-L+1)]^t$, $e(n) = d(n) - \mathrm{w}^t(n)\, \mathrm{x}(n)$, with $d(n)$ being so-called the desired response available during initial training period and μ denoting so-called the step-size parameter.

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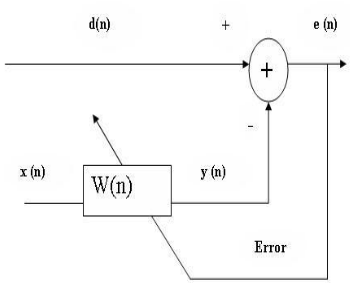

Fig. 1. Adaptive Filter Structure

In order to remove the noise from the ECG signal, the ECG signal $s_1(n)$ with additive noise $p_1(n)$ is applied as the desired response $d(n)$ for the adaptive filter. If the noise signal $p_2(n)$, possibly recorded from another generator of noise that is correlated in some way with $p_1(n)$ is applied at the input of the filter, i.e., $x(n) = p_2(n)$ the filter error becomes $e(n) = [s_1(n) + p_1(n)]$ ¡ $y(n)$. The filter output $y(n)$ is given by,

$$y(n) = \mathbf{w}^t(n)x(n), \tag{2}$$

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$$E[e^2(n)]=E[(s_1(n) - y(n))^2]+E[p_1^2(n)] \tag{3}$$

In FXLMS algorithm the filtered version of $x(n)$ is used for weight update process, i.e., the forward path is introduced between the input signal and the algorithm for the adaptation of the coefficient vector. The transfer function of the forward path is assumed to be an I-th order finite impulse response (FIR) system $A(z) = a_0 + a_1 z^{-1} + ... + a_I z^I$. Now the estimation error $e(n)$ can be written as,

$$e(n) = d(n) - \sum_{i=0}^{I-1} a(i) \sum_{l=0}^{L-1} w_l(n-i)\, x(n-i-l) \tag{4}$$

According to the FXLMS algorithm, the filter coefficients are adapted according to the following recursion:

$$w(n+1)= w(n)+ \mu x'(n)e(n) \tag{5}$$

where $x'(n) = [\, x'(n), x'(n-1), \ . . , x'(n-L+1)\,]^t$ and

$$x'(n) = s(n) * x(n) \tag{6}$$

The output of the adaptive filter is computed as,

$$x''(n) = w(n) * x'(n) \tag{7}$$

It is clear from (6) and (7) that the computation of FXLMS algorithm involves two convolution operations and can be computed efficiently using block processing.

III. SIMULATION RESULTS

To show that FXLMS algorithm is really effective in clinical situations, the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. We used the benchmark MIT-BIH arrhythmia database ECG recordings as the reference for our work and real noise is obtained from MIT-BIH Normal Sinus Rhythm Database (NSTDB). The arrhythmia data base consists of 48 half hour excerpts of two channel ambulatory ECG recordings, which were obtained from 47 subjects, including 25 men aged 32-89 years, and women aged 23-89 years. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10mV range. In our simulation we collected 4000 samples of ECG signal, a random noise with variance of 0.001 was added to the ECG signals to evaluate the performance of the algorithm. Through out the work step-size parameter μ is chosen as 0.01 and the filter length is 5. Table I shows MSE of the both algorithms in dBs. For the evaluating the performance of the proposed adaptive filter we have measured the SNR improvement and compared with LMS algorithm. Table II gives the contrast of the both algorithms in SNR. From computed SNR values it is clear that the FXLMS algorithm performs better for the removal of non stationary noise like base line wander, muscle artifacts and motion artifacts.

TABLE- I
MSE OF BOTH ALGORITHMS

Algorithm	MSE(dBs)
LMS	-7.7615
FXLMS	-8.1326

A. *Baseline Wander Reduction*

In this experiment, first we collected 4000 samples of ECG signal corrupted with natural baseline wander (data105), is applied as primary input to the adaptive filter of Fig.1. A low amplitude synthetic BW is generated with frequency 0.5Hz and is applied as the reference input to the adaptive filter. The adaptive filter was implemented using the LMS and FXLMS algorithms to study the relative performance and results are shown in Fig.2. The LMS algorithm gets SNR improvement 2.5568dB, where as FXLMS gets 3.6111dB.

B. *Adaptive Power-line Interference Canceler*

To demonstrate power line interference cancelation we have chosen MIT-BIH record number 105. The input to the filter is ECG signal corresponds to the data 105 corrupted with synthetic PLI with amplitude 1mv and frequency 60Hz, sampled at 200Hz. The reference signal is synthesized PLI, the output of the filter is recovered signal. These results are shown in Fig.3. In SNR measurements it is found that FXLMS algorithm gets SNR improvement 7.2387dB, where as the conventional LMS algorithm improves 9.1852dB. Fig.4 shows the power spectrum of the noisy signal before and after filtering with FXLMS algorithm. No harmonics are synthesized. From the spectrum it is clear that the adaptive filter based on FXLMS filters the PLI efficiently.

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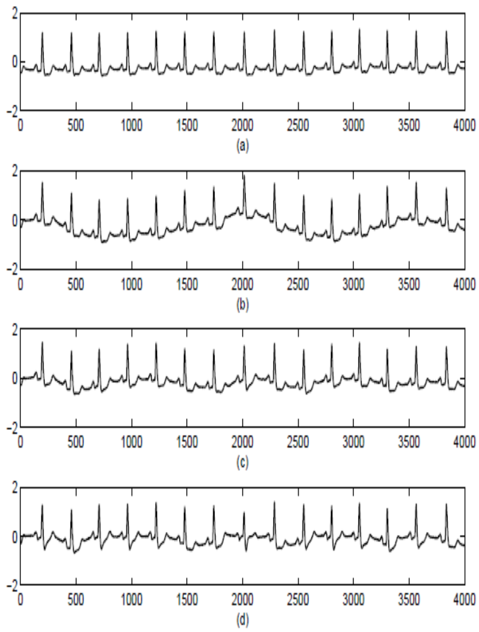

Fig. 2. Typical filtering results of baseline wander reduction (a) MIT-BIH record 105, (b) MIT-BIH record 105 with natural baseline wander,(c) recovered signal using LMS algorithm, (d)recovered signal using FXLMS algorithm.

C. Adaptive Cancellatioin of muscle artifacts

To show the filtering performance in the presence of non-stationary noise, real muscle artifact(MA)was taken from the MIT-BIH Noise Stress Test Database (NSTDB). This database was recorded at a sampling rate of 128Hz from 18 subjects with no significant arrhythmias. The MA originally had a sampling frequency of 360Hz and therefore they were anti-alias resampled to 128Hz in order to match the sampling rate of the ECG. The original ECG signal with MA is given as input to the adaptive filter. MA is given as reference signal. The output from the filter is noise free signal. These results are shown in Fig.5. The SNR improvement of FXLMS algorithm is 2.1337dB and conventional LMS algorithm gets 1.5221dB.

D. Adaptive Motion Artifacts Cancellation

To demonstrate this we use MIT-BIH record number 105 ECG data with electrode motion artifact (EM) added, where EM is taken from MIT-BIH NSTDB. The ECG signal corresponds to record 105 is corrupted with EM is given as input to the adaptive filter. The EM noise is given as reference signal. Output of the filter is filtered signal. Fig.6. shows these results. The SNR improvements for FXLMS algorithm is 3.5491dB, that for conventional LMS algorithm are found as 2.2362dB.

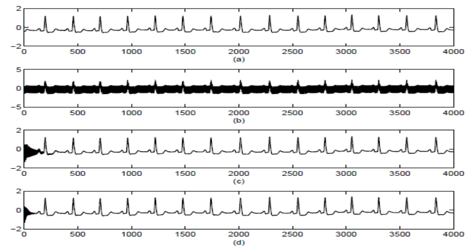

Fig. 3. Typical filtering results of PLI reduction (a) MIT-BIH record 105, (b) MIT-BIH record 105 with PLI,(c) recovered signal using LMS algorithm, (d)recovered signal using FXLMS algorithm.

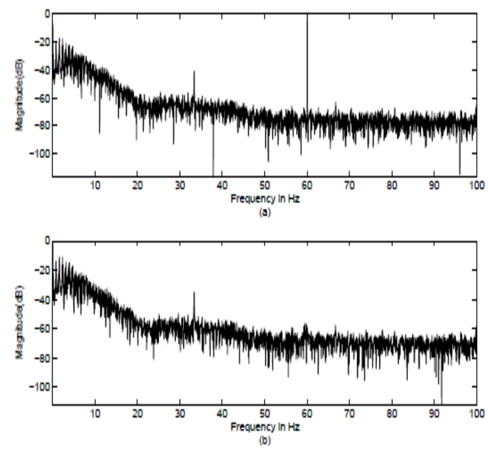

Fig. 4. (a) Frequency spectrum of ECG with PLI, (b) Frequency spectrum after filtering with FXLMS algorithm.

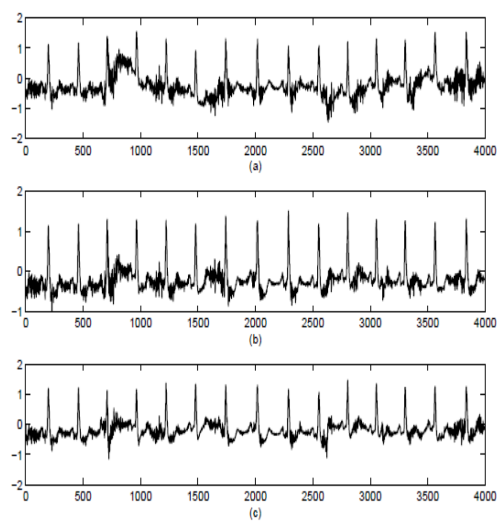

Fig. 5. Typical filtering results of muscle artifacts removal (a) ECG with real muscle artifacts, (b) recovered signal using LMS algorithm, (c) recovered signal using FXLMS algorithm.

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TABLE- II
PERFORMANCE CONTRAST OF VARIOUS ALGORITHMS FOR THE CANCELLATION OF ARTIFACTS (ALL VALUES ARE IN DECIBELS)

Type of Noise	Record No.	LMS	Filtered-X LMS
BW	100	2.5555	3.6695
	105	2.5976	3.9640
	108	2.2876	3.4254
	203	3.4976	3.6293
	228	1.8457	3.3674
	Avg.	2.5568	3.6111
PLI	100	7.7652	9.1522
	105	7.7564	9.0460
	108	7.7679	9.1413
	203	7.7525	10.3821
	228	5.1519	9.1852
	Avg.	7.2387	9.1852
MA	100	1.3443	1.9164
	105	1.4448	2.1945
	108	1.3288	2.0488
	203	2.1447	2.1281
	228	1.3483	2.3809
	Avg.	1.5221	2.1337
EM	100	2.1551	3.4085
	105	2.4654	3.9401
	108	1.9914	3.2841
	203	2.9587	4.0575
	228	1.6107	3.0553
	Avg.	2.2362	3.5491

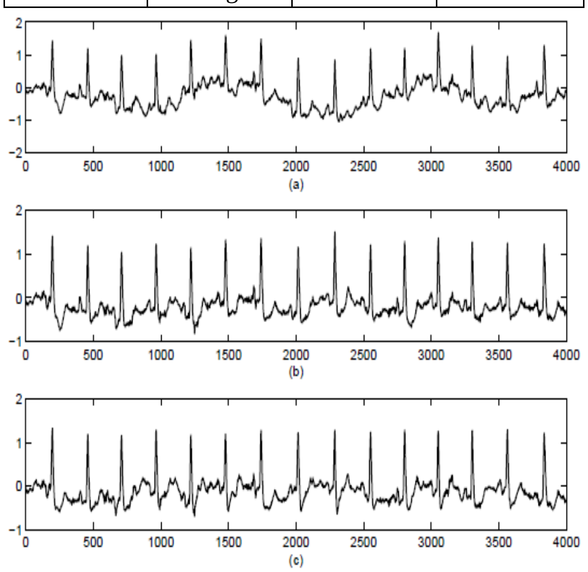

Fig. 6. Typical filtering results of motion artifacts removal (a)ECG with real motion artifacts, (b) recovered signal using LMS algorithm, (c) recovered signal using FXLMS algorithm.

CONCLUSIONS

In this paper the process of noise removal from ECG signal using FXLMS based adaptive filtering is presented. For this, the input and the desired response signals are properly chosen in such a way that the filter output is the best least squared estimate of the original ECG signal. The proposed treatment exploits the modifications in the weight update formula and thus pushes up the speed-up over the respective LMS based realizations. Our simulations, however, confirm that the SNR of the FXLMS based adaptive filter is better than that of LMS based adaptive filter. Table I clears that filtering capability of FXLMS is better than LMS algorithm.

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